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AI-based audit acceptance and auditors' technology readiness

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A B S T R A C T

This study investigates auditors' willingness to adopt AI-based audit tools using the AI Device Use Acceptance (AIDUA) model, focusing on the factors influencing acceptance and the moderating role of technology readiness. Data were collected from 153 certified external auditors in Jordan, representing a 30% response rate. The findings reveal that social influence and hedonic motivation positively impact performance expectancy, while anthropomorphism influences effort expectancy. Emotions significantly affect auditors' willingness to adopt AI-based audits, moderated by their technology readiness. This study contributes to the literature by utilizing the AIDUA framework to understand AI acceptance in auditing, offering insights into the unique aspects of AI technologies. The results highlight the importance of understanding auditors' perceptions and readiness, providing valuable implications for practitioners and policymakers to develop strategies for effective AI integration in auditing. Future research should explore these dynamics in diverse cultural contexts and over extended periods to enhance the generalizability of the findings.

1. Introduction

The expansion of artificial intelligence (AI) has notably impacted the domain of accounting and auditing worldwide (Han et al., 2023; Zhang et al., 2022; Al-Sayyed et al., 2021; Munoko et al., 2020; Mohammad et al., 2020). This impact has been characterized by improvements in accuracy and data quality (Truong and Papagiannidis., 2022; Erasmus & Marnewick, 2021). Audit firms can effectively leverage the capabilities of AI through several methods. These include automating mundane tasks, integrating predictive analytics, employing AI tools and audit processes, utilizing blockchain technology, and implementing AI-driven chatbots (Abdullah & Almaqtari, 2024). These strategies are anticipated to result in enhanced audit quality, streamlined operations requiring fewer personnel, and reduced auditing costs (Thottoli et al., 2022; Fedyk et al., 2022). Integrating AI into auditing procedures facilitates the analysis of extensive financial datasets and the detection of patterns (Lehner et al., 2022), leading to heightened productivity and reduced risk of errors (Thottoli, 2024). Moreover, AI enhances the audit process by providing functionalities like fraud detection, risk assessment, and predictive analytics (Seethamraju & Hecimovic, 2022; Al Natour et al., 2024a). Consequently, the automation of auditing procedures is increasingly regarded as essential for maintaining competitiveness in today's dynamic business landscape (Chukwuani & Egiyi, 2020). Overall, AI-driven systems empower auditors to remain competitive within the marketplace (Agustí & Orta-Pérez, 2022; Al Wael et al., 2024).

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The advancement of technology and digitalization is bringing about a substantial transformation in accounting, auditing, and finance (Damerji & Salimi, 2021; Kommunuri, 2022). The emergence of AI is driving significant changes in the accounting industry, reshaping how accounting, finance, audit, and advisory services are delivered. Contemporary accounting practices increasingly rely on data-driven methodologies, automation, and intelligent systems rather than traditional information systems. These modern intelligent systems have resulted in noteworthy changes in auditing, impacting the roles and responsibilities of both human and AI-based entities. This underscores the crucial role of AI as a promising direction for the future of the accounting and auditing professions (Kommunuri, 2022).

The application of AI-based technologies in accounting and auditing is still in its early stages, with limited focus on examining their role, relevance, and impact in these areas (Mancini et al., 2021). Insufficient consideration is also given to the role and relevance of these technologies within the auditing landscape (Kommunuri, 2022). Moreover, there are significant concerns regarding human adaptability and the development of interactions between humans and machines, with notable implications for the future of auditing in the AI era (Moll & Yigitbasioglu, 2019). Consequently, research into the utilization of AI in auditing and how auditors can harness these technologies to enhance performance is still in its infancy. Furthermore, there is a need for better understanding of the factors influencing auditors' readiness to adopt AI in auditing and the optimum utilization of these technologies within the sector.

The integration of AI has a substantial impact on the planning, execution, and reporting of audits (Khan et al., 2021). Incorporating AI into auditing is more complex than traditional IT tools, largely due to the use of advanced technologies such as natural language processing and machine learning, which are crucial for processing large volumes of data at high speeds and with diverse characteristics (Çabuk & Aytaç, 2019). This complexity has hindered the widespread adoption of AI in auditing (Mahzan & Lymer, 2014). Additionally, conventional IT acceptance models like TAM and UTAUT are not entirely suitable for studying AI technologies, as noted by Gursoy et al. (2019). Consequently, they introduced the AIDUA model to address the limitations of these traditional models in assessing the acceptance of AI tools. Despite these advancements, there is still a need for further exploration of the state-of-the-art AI adoption and the implementation of the AIDUA model among auditors. In light of this, the present study aims to bridge this knowledge gap by examining auditors' readiness to embrace AI-based auditing practices through the AIDUA framework. Therefore, the research seeks to achieve specific objectives.

QR 1: To investigate the willingness to accept the use AI-based audit based on AIDUA.

QR2: To investigate the moderating effect of auditors' technology readiness.

The convergence of AI and accounting challenges both challenges and opportunities for researchers, business owners, and administrators (Ghura & Harraf, 2021). In the wake of recent shifts in the global economy, the influence of AI on the advancement of the accounting industry is becoming increasingly apparent (Mohmmad et al., 2020). There is across-the-board recognition in the literature of the hurdles confronting current accounting and auditing practices (Han et al., 2023). Hence, this paper reexamines the use of AI-based auditing, driven by the imperative to gain a comprehensive understanding of the context of AI integration in the field of auditing inspired by earlier literature (Zhang et al., 2022; Kommunuri, 2022; Goto, 2023).

This research makes a significant contribution to the existing literature on accounting and auditing by broadening the scope of research on the integration of AI within these fields. It adds to the growing literature on AI-based audits and investigates the acceptance of AI-based audit, drawing on the AIDUA assumptions. This exploration deepens our understanding of the implications and benefits of incorporating AI into audit development. The findings of this research contribute to the ongoing discussion on the adoption and use of AI in auditing practices. Furthermore, this research offers valuable insights for the field by contributing to the interpretation of auditors' responses and the outcomes of advanced AI models. The paper presents a variety of techniques that have the potential to enhance the interpretability of AI-based audits, serving as a catalyst for future research in this domain. It addresses a gap in the literature by establishing a direct connection between the concept of AIDUA and auditing practice and research. By introducing the latest knowledge on the acceptance of AI-based audits to auditing professionals, it bridges the gap between theory and practice. Additionally, this paper meets the demand for practice-oriented research in accounting by offering practical methods and guidelines that researchers and practitioners can use to improve the interpretability of their AI applications. Policymakers can also leverage this document as a valuable resource for promoting appropriate AI-based audit practices. The paper is structured as follows: section 2 provides an overview of the literature related to AI and AIDUA, while section 3 explores the research model and hypothesis development. Section 4 describes the research methodology used in the study, followed by the presentation of analysis and results in section 5, and a thorough discussion in section 6. The study concludes with a summary, limitations, and suggestions for future research.

2. Literature review

2.1 AI-based Accounting and Auditing

AI, as delineated by various scholars, is understood as the capability of an artificial entity to perform tasks by exceeding or meeting requirements while being sensitive to cultural and demographic factors (Kelly et al., 2023; McLean & Osei-Frimpong, 2019). Meyer-Waarden and Cloarec (2021) describe AI as machines and systems capable of executing tasks traditionally dependent on human intelligence, thereby precipitating a swift evolution in the marketing sector. Xian (2021) views AI as the capability of a machine to accumulate data, apply complex algorithms, and learn from this data, thus adapting and expanding its capabilities. Russell and Norvig (2020) describe AI as the capability of machines to demonstrate human-like intelligence, including perception, reasoning, learning, and interaction. Similarly, Rai et al. (2020) define AI as a machine's ability to perform cognitive functions commonly associated with the human brain, such as perception, reasoning, learning, environmental interaction, problem-solving, decision-making, and even creativity. Despite the long-standing presence of the field, there is still no consensus on a definitive definition of AI (Collins et al., 2021). For the purposes of this study, AI is used as an umbrella term encompassing technologies that can collect, analyse, and manage both structured and unstructured data, enabling the automation of digital and physical tasks and processes (Rikhardsson et al., 2022). AI is gaining increasing attention for its potential applications in the field of auditing (Zhang et al., 2022). Audit firms are compelled to innovate their services in response to the emergence of AI (Thottoli, 2024). In this context, AI can impact the auditing process in two main ways (Rikhardsson et al., 2022). Firstly, the integration of AI into audit clients' operations introduces risks, including operational and financial risks such as data breaches, improper data usage, and reputational risks associated with AI biases. While some research has explored this impact, particularly from an internal auditing viewpoint (Chan & Kim, 2020; Applegate & Koenig, 2019), there is relatively limited literature on these issues from the viewpoint of external auditing (Rikhardsson et al., 2022). Secondly, AI is poised to significantly enhance both the effectiveness and efficiency of the audit procedure. Tudor and Deliu (2022) observe that new AI technologies are transforming auditing services, notably in terms of digital workplace integration and process workflow optimization (Moll & Yigitbasioglu, 2019). These technologies also necessitate a deeper understanding of clients' digitalized business models (Commerford et al., 2022). Moreover, AI is diminishing the labor-intensive aspects of certain audit tasks, thus shifting the focus towards more efficient advisory and consulting services (Greenman, 2017; Kokina & Davenport, 2017). Consequently, because of technological advancements, certain levels, activities, and responsibilities within the audit profession may diminish while others expand. In this context, there are still unanswered questions about which audit tasks are better suited for algorithms compared to human involvement (Tudor & Deliu, 2022). The available research on AI-based auditing indicates a variety of investigations into the implementation of AI in auditing, employing numerous theoretical frameworks. Abdullah and Almaqtari (2024) highlight the advantages of utilizing AI and big data analytics to enhance the auditing methods, as these technologies are instrumental in boosting accuracy, efficiency and decision-making capabilities, which in turn significantly enhance auditing procedures. Al-Wael et al. (2024) noticed that factors such as organizational culture, regulatory support, perceived usefulness, and ease of use play crucial roles in the adoption of AI within the public accounting sector in Kuwait. Han et al. (2023) noted that the implementation of multiparty proof in blockchain protocols provides auditors with real-time and dependable data, thereby improving assurance and efficiency. Similarly, Oduwole and Olukunle (2023) discovered that automation processes, expert systems, and intelligent agents have a substantial impact on the accounting procedures in the banking sector. Furthermore, Kommunuri (2022) proposed that AI, specifically robotic process automation, will replace audit data standards with minimal programming required. Additionally, the integration of AI, such as machine learning methods and other computer-assisted tools, can improve fraud detection by incorporating a wide range of explanatory variables into models. Commerford et al. (2022) indicated that auditors often exhibit a bias known as "algorithm aversion", where they place undue trust in evidence from human specialists. This bias should be carefully considered when implementing AI in auditing firms. Additionally, Tudor and Deliu (2022) outlined the utilization of AI throughout different phases of the audit process. In the planning phase, AI gathers initial information about the customer and their activities, collecting, aggregating, and analysing data from financial statements, operational processes, and organizational structure. In the contracting phase, AI estimates the duration of the engagement and calculates audit fees. Moving forward, AI evaluates the client's internal control and risk factors, identifying instances of fraud. Any anomalies detected are reported using flowcharts, narratives, and questionnaires. Finally, based on AI's findings, conclusions are drawn (Issa et al., 2016). By allocating more time to providing insights and exercising professional judgment, auditors can enhance the quality of their work (Greenman, 2017). The incorporation of AI in audit procedures greatly improves the sufficiency of audit evidence by automating tasks like full-population examination (No et al., 2019). However, when AI is utilized for functions like anomaly detection or predictions, auditors must assess the relevance of the assertions in relation to the AI-generated outputs and the reliability of these results (Zhang et al., 2022).

2.2 Technology Readiness

Technology Readiness (TR) was developed to explain the psychological factors influencing an individual's willingness to adopt and utilize modern technologies in both personal and professional settings (Parasuraman, 2000). TR evaluates how prepared a person is to embrace new technologies by assessing their overall mindset, which is shaped by various mental factors that either encourage or impede technology adoption (Parasuraman, 2000). Lai and Chen (2008) expanded on this by noting that an individual's perceptions of a specific technology contain both positive and negative elements, which together determine their readiness to adopt it. Positive perceptions motivate individuals towards new technologies, while negative perceptions discourage them (Parasuraman & Colby, 2015). Parasuraman and Colby (2015) and Parasuraman (2000) suggested that these beliefs can be divided into different dimensions, such as optimism and innovativeness (positive dimensions or facilitators), as well as discomfort and insecurity (negative dimensions or barriers) (Damerji & Salimi, 2021). According to the International Federation of Accountants (IFAC, 2018), professional accountants are required to have essential IT skills. In auditing, it is essential for external auditors to demonstrate readiness in technology to carry out their responsibilities efficiently (Al Natour et. al., 2024b). Some researchers have suggested that the technological readiness of external auditors could impact their competencies to a certain degree (Jaffar et al., 2022).

3. Research Model and hypotheses development

3.1 Theoretical basis

It is essential for stakeholders to comprehend user acceptance to determine the necessary elements for promoting technology adoption across various settings (Kelly et al., 2023). To assess user acceptance of AI, multiple theoretical models have been utilized, such as the TAM (Davis, 1985), UTAUT (Venkatesh et al., 2003), and AIDUA (Gursoy et al., 2019). The TAM originally introduced based on the Theory of Reasoned Action (Ajzen & Fishbein, 1975), posits that external factors like media and societal influences shape an individual's views on the usefulness (PU) and simplicity (PEOU) of technology. These views then influence their intent to use the technology and, eventually, their actual usage (Davis, 1989).

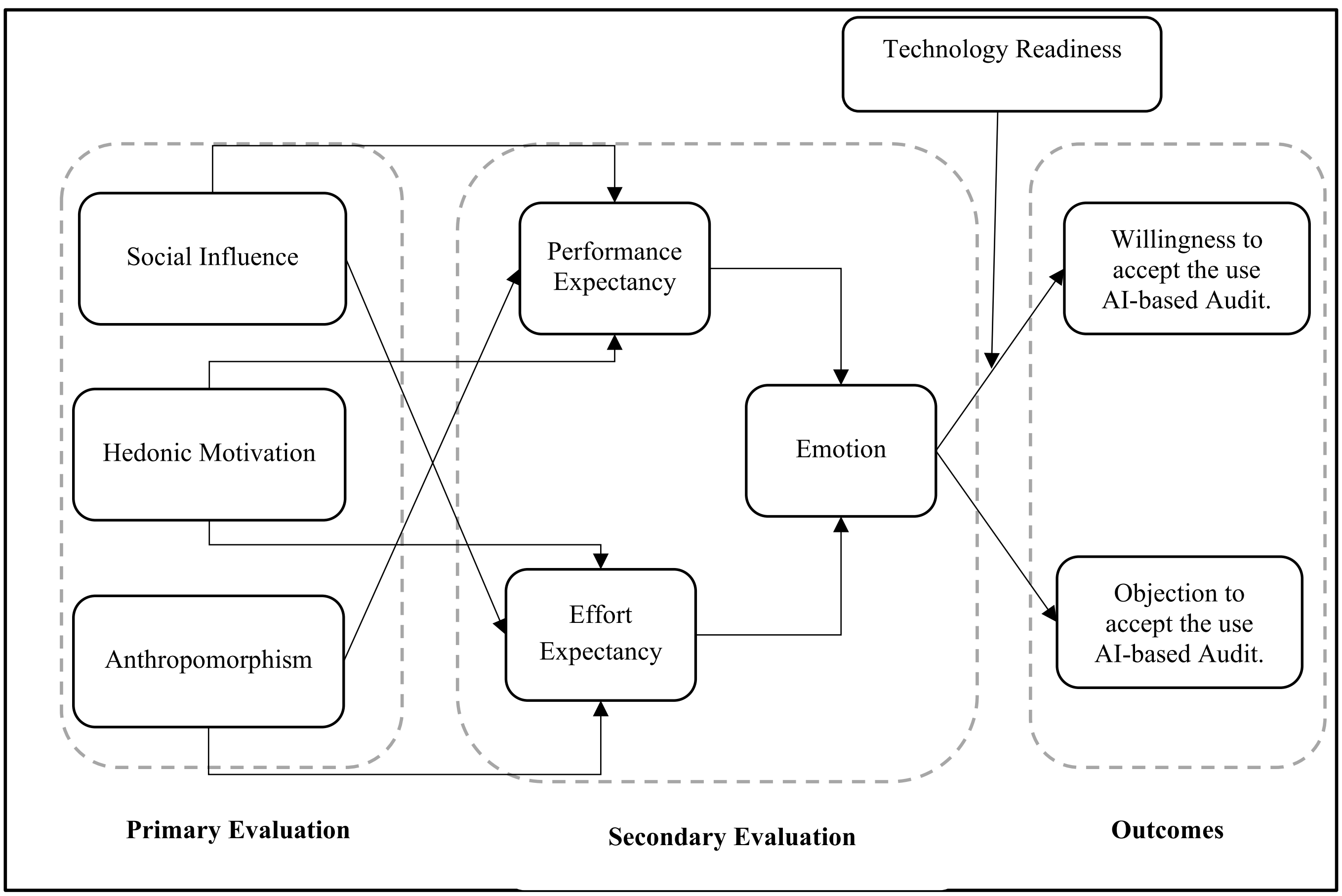

Fig. 1. The proposed conceptual framework

Additionally, while TAM has been broadly endorsed as a substantial model for analyzing technology adoption, the swift progression of AI technologies has put its predictive strength to the test (Sohn and Kwon, 2020). Lu et al. (2019) indicated that certain core elements of technology acceptance models, for instance perceived usefulness (PU) and perceived ease of use (PEOU), might not be directly relevant in the context of AI device usage intentions. When considering AI devices, users typically assess whether these technologies can match or exceed the performance of human staff. Thus, it is critical to utilize theoretical frameworks that are specifically designed to assess AI acceptance to increase the accuracy of predictions. In response, the AI Device Use Acceptance model (AIDUA) was developed to examine how users accept AI technology (Gursoy et al., 2019). AIDUA builds upon earlier models by examining the user experience through three stages: primary appraisal, secondary appraisal, and outcome stage. In the primary appraisal phase, users assess the importance of AI devices by considering factors such as social influence, hedonic motivation, and anthropomorphism (Gursoy et al., 2019). In the secondary appraisal phase, users evaluate the advantages and drawbacks of the AI device by considering its performance expectancy and effort expectancy, which in turn affects their emotional responses to the AI (Gursoy et al., 2019). These appraisals lead to the outcome stage, where users decide to either accept or reject the technology (Gursoy et al., 2019). This model uniquely identifies that acceptance and rejection are not necessarily contradictory, offering valuable insights for researchers (Kelly et al., 2023). In this study, the AIDUA model is employed to examine the adoption of AI-enhanced audit methods and the inclinations of external auditors to incorporate these technologies. The proposed conceptual framework is illustrated in Fig. 1. PU is about how users perceive the advantages a technology brings to their everyday activities (Davis, 1989), while PEOU deals with their perception of the ease with which a technology can be used (Davis, 1989). To boost its predictive power, TAM is frequently enhanced with other variables (Lin & Xu, 2021; Kashive et al., 2021). For example, Choung et al. (2022) expanded the TAM and identified a positive link between trust and PU. The UTAUT was developed by synthesizing elements from different acceptance theories, containing the TAM (Venkatesh et al., 2003). UTAUT theorizes that performance expectancy, social influence, effort expectancy, and facilitating conditions are key determinants of behavioural intentions, which in turn affect actual technology usage (Venkatesh et al., 2003). The model also indicates that factors such as age, gender, and previous experience can modify how these determinants impact intentions and usage (Venkatesh et al., 2003). Various studies have demonstrated that UTAUT can explain up to 70% of the differences in behavioral intentions across different cultural settings (Thomas et al., 2013). In the field of accounting, UTAUT has been utilized to investigate the adoption of new technological systems, such as cloud-based accounting solutions (Dwivedi et al., 2019).

3.1 AIDUA three-stages toward adoption or objection AI

Lazarus et al. (1991) introduced a model that delineates how individuals navigate through various stages of appraisal during decision-making processes. This includes assessing the significance of the stimulus (primary appraisal), considering possible actions (secondary appraisal), and forming emotions that shape behavioral intentions (Gursoy et al., 2019). Initially, in the primary appraisal stage, individuals evaluate the significance of utilizing AI devices based on factors such as social influence, hedonic motivation, and anthropomorphism (Gursoy et al., 2019). These factors are anticipated to enhance performance expectancy and reduce effort expectancy at this stage (Gursoy et al., 2019). According to Social Impact Theory (Latané, 1981), individuals are inclined to adhere to group norms if they value the group highly. Studies indicate that norms and attitudes within one's social network significantly shape one's behavioral intentions (Rather, & Hollebeek, 2019). Accordingly, if a social network that includes colleagues, or family members holds favorable views towards AI devices and supports their use in service delivery, this positive social influence can boost individuals' propensity to adopt AI devices. Furthermore, various empirical studies have explored the concepts of social norms and perceived ease of use (Hall & Henningsen, 2008; Gursoy et al., 2019). Therefore, if the auditors social circle's view AI devices as user-friendly, auditors are likely to perceive these devices as less complex to operate. Thus, H1 and H2 were developed as follows.

H_1: *There is a positive relationship between social influence and perceived Performance Expectancy of AI.*

H_2: *There is a negative relationship between social influence and effort expectancy of AI.*

Existing studies suggest that hedonic motivation significantly impacts the behavior related to technology adoption (Law et al., 2018; Venkatesh et al., 2012). When individuals experience hedonic motivations toward AI devices, their usage is propelled by personal interests, the allure of novelty, and the pursuit of enjoyment (Gursoy et al., 2019; Fryer et al., 2017). Consequently, auditors who are influenced by hedonic reasons when using AI devices generally maintain a favourable attitude towards their usage. Furthermore, research has established a link between motivation and the perceived ease of technology use (Capa et al., 2008; Gendolla & Wright, 2005; Wright & Kirby, 2001). Based on these insights, hypotheses H3 and H4 were formulated.

H_3: *There is a positive relationship between hedonic motivation and perceived Performance Expectancy of AI.*

H_4: *There is a negative relationship between Hedonic motivation and effort expectancy of AI-based Audit.*

Research by Lu et al. (2019) and van Doorn et al. (2017) indicates that anthropomorphism significantly impacts how consumers interact with AI devices. Individuals who attribute human-like qualities to AI devices may perceive them as threatening their personal uniqueness and self-identity (Rosenthal-von der Pütten & Krämer, 2014). Studies involving social robots show that people tend to react more favourably to robots that exhibit only partial human-like features as opposed to fully human appearances (Goudey & Bonnin, 2016). These human-like attributes in AI devices can provoke concerns over personal identity (Gursoy et., 2019), causing individuals to voice their reservations based on assumptions that these devices might underperform. Moreover, some consumers rationalize their hesitance to employ AI for service tasks, believing that interacting with AI requires more effort than engaging with human staff. This belief stems from societal norms that suggest treating AI as sentient entities (Kim & McGill, 2018). The perception of being humanoid involves effort from two angles: the effort of interacting with a real person and the learning curve associated with new technology. Therefore, the anthropomorphic traits of AI devices could amplify the perceived effort needed for their use, covering both human and technological interactions, leading to the formulation of hypotheses H5 and H6.

H_5: *There is a negative relationship between anthropomorphism and perceived Performance Expectancy of AI.*

H_6: *There is a positive relationship between anthropomorphism and effort expectancy of AI-based Audit.*

3.1.2 Second stage- secondary evaluation

If individuals conclude that the use of AI is consistent with the norms and values upheld by their social groups, they advance to the next phase of appraisal. In this phase, they meticulously analyze the benefits and drawbacks associated with AI device usage, considering how well the devices meet performance expectations and the effort required to use them (Gursoy et al., 2019; Lazarus, 1991a). This in-depth review involves exploring possible choices and understanding the emotional repercussions of each (Gursoy, 2019). Specifically, auditors contemplate the trade-offs involved in embedding AI into their service operations, focusing on the perceived efficacy and required exertion (Venkatesh et al., 2012). This process leads to the development of auditors' emotional perspectives on using AI in delivering services. This study asserts that perceived efficacy and required exertion are pivotal in evaluating the merits and demerits of AI use. These elements are key in shaping consumers' emotional responses to AI, as identified by Lu et al. (2019). Thus, influenced by the AIDUA model, the subsequent hypotheses were established:

H_7: *There is a positive relationship between auditor's perceived performance expectancy auditors' and emotions toward the use of AI-based Audit.*

H_8: *There is a negative relationship between auditor's perceived effort expectancy and auditors' emotions toward the use of AI-based Audit.*

3.1.3 Third stage- outcomes

The final phase is characterized by users' emotional responses to AI implementations, which ultimately shape their readiness to embrace or reject AI (Gursoy, 2019). Following a detailed evaluation, emotions related to the use of AI devices are formed, impacting whether customers will accept or reject these devices in service interactions. The term "willingness to accept" refers to the extent to which customers are prepared to utilize AI devices in upcoming service situations. Studies indicate that positive emotional responses, including feelings of anticipation, satisfaction, happiness, enjoyment, delight, and surprise, play a crucial role in influencing consumer behaviors (Watson & Spence, 2007). Under the Cognitive Appraisal Theory, customers who experience these positive emotions in relation to AI devices are more inclined to accept their usage in service contexts. On the other hand, the decision-making process may also evoke negative emotions such as frustration, fear, uncertainty, anxiety, and concern (Raghunathan & Pham, 1999; Rucker & Petty, 2004). According to the same theory, these negative emotions can lead to the refusal of certain products or services. From this understanding, the following hypotheses are formulated:

H_9: *There is a positive relationship between emotion and Auditors' willingness to accept the use of AI-based audit.*

H_{10}: *There is a negative relationship between emotion and Auditors' willingness to objection the use of AI-based audit.*

3.2 Moderating effect of Technology Readiness

Previous literature has explored the significance of technology readiness in shaping how individual variances impact the acceptance and use of emerging technologies (Chang & Chen, 2021; Chen & Lin, 2018; Kaushik & Rahman, 2017; Nugroho & Fajar, 2017). Taking an optimistic stance, a favorable attitude towards innovative technologies can improve user adaptability, control, and effectiveness (Chang & Chen, 2021). Generally, individuals with a high level of technology readiness demonstrate proficiency, enthusiasm, and ease with new technologies, encountering fewer technical challenges. Conversely, those with lower technology readiness tend to exhibit doubt, reluctance, and reservations when it comes to embracing latest technologies (Wang et al., 2017). While many studies have considered technology readiness as a direct driver of technology-related attitudes and adoption rates (Chen & Lin, 2018; Kaushik & Rahman, 2017), others have regarded it as a moderating factor. For instance, Borrero et al. (2014) categorized participants into high-TR and low-TR groups to keep differences in the proposed connections. Furthermore, as an individual trait, technology readiness can influence the interplay between user motivations and their intentions to take action (Chao and Yu, 2019; Wang et al., 2017). The research referenced provides valuable insights into the technology readiness (TR) of individuals in the accounting profession. According to Ming-Ling and Muhammad (2006), Malaysian tax officers showed a general favorable attitude towards new technologies, but also expressed some unease in using them. The study also observed that male tax officers were more optimistic about technology compared to their female counterparts. Ramen and Jugurnath (2015) developed a comprehensive model that linked TR with various elements to examine the adoption of computer-assisted audit techniques (CAATs) within audit firms. Their findings revealed positive associations with perceived usefulness, ease of use, facilitating conditions, social influence, and motivation, while inhibitory beliefs negatively affected CAAT adoption. Furthermore, Bhushan et al. (2017) emphasized the efforts made by accounting firms to enhance TR among their staff through computer training and updated accounting software. Alkhaffaf et al. (2018) examined the effect of TR on individual capabilities among accountants in relation to IT usage at work, and they recovered a strong positive connection between TR and IT proficiency. Additionally, Ilias et al. (2020) assessed the readiness of accounting practitioners in Malaysia, including their optimism, innovativeness, discomfort, insecurity, and their overall Technology Readiness Index (TRI). Their results indicated that practitioners generally held an optimistic view toward adopting new technologies.

Based on these insights, this study suggests utilizing TR as a moderating variable on the association between emotions and the acceptance of AI-based auditing technologies. It proposes that individuals with higher TR levels may be more open to AI-based audit technologies, while those with lower TR levels may exhibit more resistance. Thus, the following hypothesis was developed:

H_{11}: *auditors' technology readiness moderates the relationship between emotions and willingness to AI-based audit acceptance.*

4. Research methodology

4.1. Population and sample

The population of this study consists of certified external auditors in Jordan. According to the Jordanian Association of Certified Public Accountants (JACPA, 2024), there are 507 external auditors in Jordan. Given the small population size, the questionnaire was self-distributed to all members of the population between February and April 2024. After several reminders and visits, 153 usable questionnaires were collected, representing a 30% response rate. This response rate is considered reasonable for survey-based studies in Jordan (Al-Momani, 2020). To ensure the adequacy of the sample size for detecting a significant effect, a power analysis was conducted using G-Power software. The analysis aimed to achieve a statistical power of 0.80, which is commonly accepted in social science research. The effect size (f^2) was set to 0.15, representing a medium effect size as per Cohen's guidelines (Cohen, 1988). The significance level (α) was set at 0.05. Using these parameters, the G-Power analysis indicated that a minimum sample size of 92 participants is required for multiple regression analysis with five predictors. The collected sample of 153 exceeds this minimum requirement, ensuring that the study has adequate power to detect medium-sized effects and reducing the risk of Type II errors. This rigorous approach to determining sample size helps ensure the reliability and validity of the study's findings.

4.2 Variable measurements and data collection

The instrument employed to measure each of the constructs in this investigation consisted of three sections. The initial section outlined the study's objectives, seeking participants' willingness to take part. The subsequent section inquired about participants' background, including their experience, occupation, and gender. The final section contained queries designed to gauge the study's variables, with each aspect measured using reflective items. In this research, a self-administered survey was developed to gather data and test the hypotheses formulated. A seven Likert scale was used to assess the level of agreement among external auditors in Jordan regarding specific statements, a common approach in social science studies (Jebb et al., 2021). The study's variables were measured based on earlier studies. Social Influence (SI) was evaluated using five items adapted from the works of Lu et al. (2019) and Venkatesh et al. (2012). Hedonic Motivation (HM) was assessed through four items from the same sources. Anthropomorphism (A) was measured with four items adapted from Lu et al. (2019). Performance Expectancy (PE) was gauged using four items from Lu et al. (2019). Effort Expectancy (EE) was assessed through three items from Lu et al. (2019). Emotions/Affects (E) were measured with six items from Lu et al. (2019). Willingness to Accept the Use of AI Devices (W) was evaluated through three items adapted from the works of Venkatesh et al. (2012) and Lu et al. (2019). Objection to the Use of AI Devices (O) was measured with three items from Wirtz et al. (2018). Readiness (R) was assessed through five items adapted from Holt et al. (2007). The measurement items can be found in the Appendix.

4.3 Common method bias

This research employed Herman's single-factor model to examine common method bias (CMB), and the analysis revealed a CMB percentage of 38.45%, which is below the suggested limit of 50%. This suggests that there is no significant issue with CMB in the study. Multicollinearity was tested utilizing variance inflation factors (VIF), the results implied that and all VIF values were found to be less than 5, implying no notable concerns regarding multicollinearity. A correlation matrix was also conducted to check for collinearity among latent variables, and the highest correlation coefficient observed was 0.64, which is below the recommended thresholds. To address common method bias concerns stemming from single-source data collection, the study followed the recommendations of Kock and Lynn (2012) and Kock (2015), and the results showed that VIF values were less than 3.3, representing no bias from the single-source data. Additionally, the study incorporated the Unmeasured Latent Marker Variables (ULVM) technique to further examine CMB. Utilizing the Smart-PLS algorithm analysis, an evaluation of R square (R2) values with and without unmeasured marker variables was conducted, and the outcomes suggested minimal variation, affirming the absence of substantial concerns regarding CMB/CMV in the study. These comprehensive assessments, drawing on both the full collinearity assessment method and ULVM, collectively reinforce the validity of the results and underscore the diligence employed to address potential biases in the research methodology.

5. Analysis and Results

5.1 Measurement model

The measurement model demonstrated a satisfactory fit with the data. The standardized root mean square (SRMR) index, which Henseler et al. (2016) suggest should be under 0.08, registered at 0.062 in this analysis, indicating a robust fit, particularly for sample sizes above 100 as noted by recent findings from Cho et al. (2020). The normed fit index (NFI) achieved a value of 0.903, exceeding the benchmark set by Henseler et al. (2016). Additionally, the measurement model's internal consistency, convergent validity, and discriminant validity were evaluated. Internal consistency was assessed using factor loadings, with a cut-point of 0.70 proving reliability, as suggested by Hair et al. (2019). Convergent validity was appraised based on three criteria from Hair et al. (2019): factor loadings above 0.70, composite reliability above 0.70, and average variance extracted (AVE) above 0.50. The initial evaluation identified items (SI4, E2, and R4) with loadings under the 0.7 threshold, leading to their removal in subsequent analyses. The outcomes of the second evaluation reaffirmed the constructs' convergent validity. Table 1 shows that the essential benchmarks for convergent validity and reliability have been satisfied.

Table 1
Reliability and Convergent Validity

Constructs/Items	Outer Loadings	Cronbach's alpha	Composite reliability	AVE
Social Influence		0.880	0.890	0.747
SI 1	0.885			
SI 2	0.898			
SI 3	0.889			
SI 4	Deleted			
SI 5	0.837			
Hedonic Motivation		0.894	0.899	0.758
HM1	0.890			
HM2	0.879			
HM3	0.857			
HM4	0.858			
Anthropomorphism		0.899	0.901	0.767
A1	0.891			
A2	0.839			
A3	0.852			
A4	0.860			
Performance Expectancy		0.893	0.895	0.757
PE1	0.753			
PE2	0.887			
PE3	0.855			
PE4	0.887			
Effort Expectancy		0.876	0.880	0.791
EE1	0.876			
EE2	0.763			
EE3	0.902			
Emotion		0.882	0.881	0.807
E1	0.754			
E2	Deleted			
E3	0.877			
E4	0.768			
E5	0.786			
E6	0.897			
Technology Readiness		0.856	0.867	0.858
R1	0.765			
R2	0.882			
R3	0.732			
R4	0.877			
R5	Deleted			
Willingness to accept the use AI-based Audit		0.902	0.905	0.904
W1	0.865			
W2	0.775			
W3	0.759			
Objection to accept the use AI-based Audit		0.887	0.897	0.812
O1	0.893			
O2	0.874			
O3	0.897			

The heterotrait-monotrait ratio of correlations (HTMT), as introduced by Henseler et al. (2015) and later modified by Franke and Sarstedt (2019), was used to evaluate discriminant validity. The general guideline is that HTMT ratios should be 0.85 or lower to confirm discriminant validity. As shown in Table 2, all HTMT ratios were below the 0.85 cutoff. This result validates the discriminant validity of the measurements, demonstrating that the constructs within the study are independent and assess distinct concepts.

Table 2
Discriminant Validity -HTMT.

Constructs	A	EE	E	HM	O	PE	R	SI	W
Anthropomorphism (A)	-								
Effort Expectancy (EE)	0.579								
Emotion (E)	0.118	0.140							
Hedonic Motivation (HM)	0.156	0.327	0.292						
Objection to accept the use AI-based Audit. (O)	0.147	0.079	0.302	0.071					
Performance Expectancy (PE)	0.117	0.414	0.234	0.655	0.123				
Technology Readiness (R)	0.119	0.143	0.636	0.311	0.260	0.250			
Social Influence (SI)	0.132	0.290	0.305	0.627	0.106	0.584	0.348		
Willingness to accept the use AI-based Audit (W)	0.097	0.138	0.655	0.341	0.301	0.275	0.648	0.308	-

5.2 The structural equation modelling.

The structural model was employed to evaluate the proposed correlations shown in Figure 2. Moreover, following the guidance of Hair et al. (2021), the structural model was analyzed using path coefficients, standard errors, t-values, and p-values, utilizing a 5,000-resample bootstrap method (Ramayah et al., 2018).

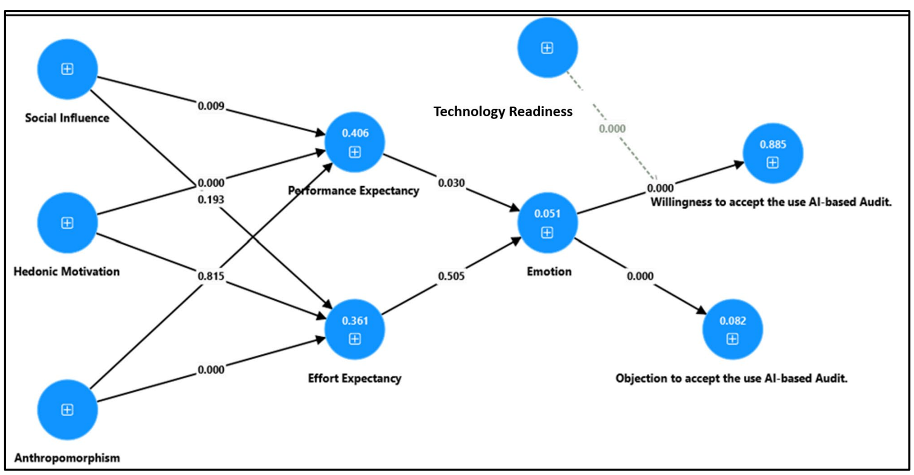

Fig. 2. The structural model

The results delineated in Table 3 elucidated several significant associations. Firstly, Performance Expectancy was positively correlated with Social Influence (H1: β= 0.208, p = 0.009) and Hedonic Motivation (H3: β= 0.441, p = 0.000). Opposite to initial expectations, Anthropomorphism did not exhibit a significant negative impact on Performance Expectancy (H5: β= 0.017, p = 0.815). Furthermore, Effort Expectancy was negatively affecting Hedonic Motivation (H4: β= - 0.168, p = 0.040) and positively correlated with Anthropomorphism (H6: β= 0.509, p = 0.000). Conversely, Social Influence did not prove a significant negative impact on Effort Expectancy (H2: β= - 0.115, p = 0.193). In the second phase of AIDUA, Emotion was found to be positively affect Performance Expectancy (H7: β= 0.197, p = 0.030), but did not display the anticipated negative relationship with Effort Expectancy (H8: β= - 0.063, p = 0.505). Lastly, in the final stage of AIDUA, Emotion was positively linked to the Willingness to accept AI-based Audit (H9: β= 0.539, p = 0.000) and negatively correlated with Objection to accepting AI-based Audit (H10: β= - 0.289, p = 0.000). The findings further disclosed that an auditor's technology readiness moderates the association between emotion and the willingness to adopt AI-based audits, corroborating H11 (β= 0.086, p = 0.000). As depicted in Figure 3, it is apparent that with higher auditor technology readiness (R = +1S.D), the association between emotion and the willingness to accept AI-based audits is strengthened. In contrast, with lower auditor technology readiness (R = -1S.D), this association continues significantly positive, although somewhat weaker, as demonstrated by the slope of the red line in the figure 3. Additionally, the R^2 values for the endogenous constructs are as follows: Effort Expectancy (0.36), Performance Expectancy (0.408), Emotion (0.05), Objection to AI-based Audit Acceptance (0.082), and Willingness to Accept AI-based Audit (0.883). These values reflect the model's explanatory power.

Table 3
Direct and indirect path coefficient and hypotheses testing.

Path	Beta	T values	P values	95% confidence interval		f2	VIF	Remarks
H1: Social Influence → Performance Expectancy	0.280	2.627	0.009	0.058	0.486	0.101	1.472	Supported
H2: Social Influence → Effort Expectancy	-0.115	1.301	0.193	-0.287	0.042	0.016	1.532	Not supported
H3: Hedonic Motivation → Performance Expectancy	0.441	4.045	0.000	0.248	0.654	0.029	1.476	Supported
H4: Hedonic Motivation → Effort Expectancy	-0.168	2.058	0.040	-0.322	-0.005	0.208	1.489	Supported
H5: Anthropomorphism → Performance Expectancy	0.017	0.234	0.815	-0.108	0.148	0.000	1.028	Not supported
H6: Anthropomorphism → Effort Expectancy	0.509	7.879	0.000	0.374	0.628	0.395	1.026	Supported
H7: Performance Expectancy → Emotion	0.197	2.177	0.030	0.025	0.375	0.036	1.173	Supported
H8: Effort Expectancy → Emotion	-0.063	0.667	0.505	-0.246	0.123	0.004	1.173	Not supported
H9: Emotion → Willingness to accept the use AI-based Audit.	0.539	6.585	0.000	0.395	0.719	0.479	2.489	Supported
H10:Emotion → Objection to accept the use AI-based Audit.	-0.289	3.491	0.000	-0.443	-0.128	0.089	1.032	Supported
H11: Technology Readiness × Emotion →Willingness to accept the use AI-based Audit.	0.086	3.535	0.000	0.042	0.141	0.065	1.017	Supported

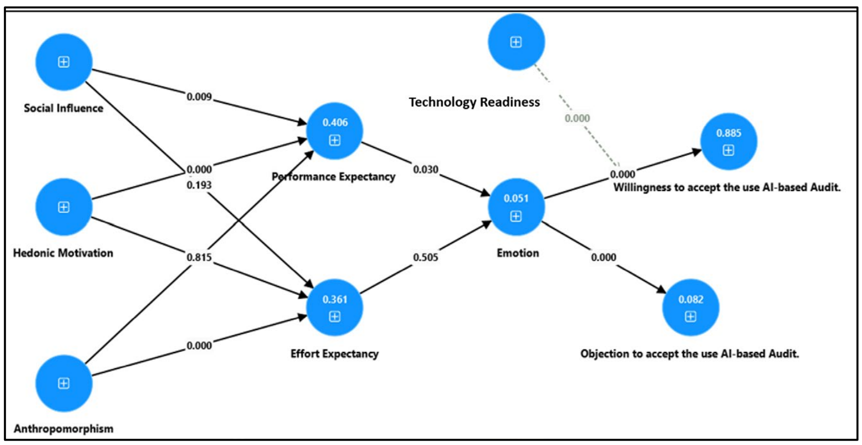

Fig. 3. The structural model

5.3 PLS-Predict

Following the recommendations of Shmueli et al. (2019), the PLS predict procedure was utilized to evaluate the model's predictive power. As demonstrated in Table 4, the PLS model exhibited lower prediction errors compared to the linear regression model (LM). Consequently, the model developed in this study demonstrated substantial predictive capability. Additionally, the predictive validity of the model was evaluated using Stone–Geisser's Q^2. The Q^2 values for the endogenous constructs were as follows: Effort Expectancy (0.329), Performance Expectancy (0.376), Emotion (0.067), and Willingness to Accept AI-based Audit (0.601). These values, with the exception of Objection to Accept AI-based Audit (0.000), are more than zero, demonstrating adequate predictive validity (Peng and Lai, 2012).

Table 4
Results of PLSpredict

items	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-SEM_RMSE-LM_RMSE
EE1	0.37	1.135	1.163	-0.028
EE2	0.25	1.254	1.302	-0.048
EE3	0.23	1.351	1.394	-0.043
O1	0.00	1.319	1.404	-0.085
O2	0.00	1.347	1.417	-0.070
O3	0.00	1.318	1.396	-0.078
PE1	0.30	1.363	1.455	-0.092
PE2	0.32	1.316	1.431	-0.115
PE3	0.22	1.329	1.397	-0.068
PE4	0.31	1.298	1.412	-0.114

RMSE indicates, the root mean square error; and LM indicates the linear regression model.

Furthermore, this study employs the cross-validated predictive ability test (CVPAT) to estimate the predictive capabilities of the path model (Liengaard et al., 2021; Sharma et al., 2023). The results, as presented in Table 5, indicate that the average loss difference values (PLS loss - Indicator Averages loss) are significantly below zero. This finding substantiates the model's superior predictive capabilities.

Table 5
CVPAT-PLS-SEM vs Indicators Average (IA)

Endogenous constructs	PLS loss	IA loss	Average loss difference	t value	p value
Effort Expectancy	1.562	2.170	-0.608	3.701	0.000
Emotion	2.227	2.369	-0.142	2.724	0.007
Performance Expectancy	1.760	2.465	-0.705	4.85	0.000
Willingness to accept the use AI-based Audit.	1.1670	2.50	-1.334	10.671	0.000
Overall	1.758	2.278	-0.52	8.432	0.000

6. Discussion

6.1 Theoretical contribution

This research significantly contributes to the AIDUA and auditing literature by utilising the AIDUA framework to analyse AI-based audit acceptance. The empirical findings demonstrate the effectiveness of AIDUA by evaluating its three stages: assessing the impact of social influence, anthropomorphism, and hedonic motivation on effort expectancy and performance expectancy; investigating the impact of effort expectancy and performance expectancy on emotion; and examining the effect of auditors' emotions on their readiness to accept or object to AI-based audit. Prior examinations have primarily focused on adoption models such as TAM and UTAUT to study the implementation of new technologies in external audit settings. However, these models primarily concentrate on functional technologies, technology-enabled services, and self-service technologies, which may not directly apply to intelligent technologies like AI (Gursoy et al., 2019; Lu et al., 2019). Thus, this research addresses a gap in the literature by investigating AI-based audit acceptance using the AIDUA framework, offering insights specifically tailored to the unique characteristics of AI technologies.

The outcomes of this research are consistent with the AIDUA framework in several respects. Specifically, the evidence supports the connections between social influence and hedonic motivation with performance expectancy, as well as hedonic motivation and anthropomorphism with effort expectancy, in line with AIDUA assumptions (Gursoy et al., 2019). Additionally, the study confirms the effect of effort expectancy on auditors' emotions and the influence of emotions on auditors' willingness to accept or object to the use of AI-based audits in accordance with AIDUA principles. However, some findings differ from the expected outcomes outlined by AIDUA. For example, the study did not support the influence of social influence on effort expectancy, nor did it find an association between anthropomorphism and performance expectancy. Moreover, it was found that effort expectancy does not directly affect auditors' emotions, contrary to AIDUA assumptions. Despite these contrasts, the general pattern of auditor behaviour regarding the acceptance or objection to AI-based audit aligns with the framework's premise, indicating that auditors react differently to new technologies in auditing, as proposed in the third stage of AIDUA.

This study contributes significantly to the existing knowledge by studying the moderating effect of auditors' technology readiness on the relationship between emotions and the willingness to accept the use of AI-based audits. By addressing this gap, the research provides valuable insights into the field, as previous research has emphasized the demand for a more profound knowledge of the factors influencing the acceptance and adoption of AI-based technologies in auditing. The study extends our understanding of how individual characteristics may influence attitudes towards AI-based audit tools, particularly regarding auditors' technology readiness. This insight can be valuable for auditing firms and policymakers in developing strategies to encourage adopting and integrating AI technologies in audit practices. Additionally, by responding to the calls for more investigation in this area, this study contributes to the ongoing dialogue on the future of auditing in the age of AI.

7. Conclusion, limitations and future research

This research thoroughly analyses auditors' willingness to embrace AI-driven auditing practices employing the AIDUA model. The outcomes reveal that social influence, hedonic motivation, and anthropomorphism significantly impact auditors' perceptions of performance and effort expectancy regarding AI technologies. Furthermore, auditors' emotional responses, influenced by these perceptions, are crucial in determining their acceptance or rejection of AI-based audits. This research underscores the significance of comprehending the distinct aspects influencing AI adoption in auditing, which differ from those related to traditional IT systems. The study also emphasizes the role of auditors' technology readiness, suggesting that higher readiness levels enhance the positive connection between emotions and AI acceptance. These findings substantially contribute to the ongoing conversation about integrating AI into auditing and deliver beneficial insights for practitioners and policymakers.

Notwithstanding its contributions, this study has several limitations. Firstly, the research is specific to auditors in Jordan, which may determine the relevancy of the conclusions to further regions or cultural contexts. Secondly, the study's cross-sectional design captures auditors' perceptions at a single point in time, potentially not fully representing changes in attitudes or behaviours over an extended period. Additionally, using self-reported data could introduce biases such as social desirability or response biases, potentially impacting the validity of the results. Moreover, while the AIDUA framework offers a robust model for understanding AI acceptance, it may only encompass some factors influencing auditors' readiness to adopt AI technologies.

It is essential for forthcoming studies to address these limitations by examining the acceptance of AI in auditing within diverse cultural and geographical contexts to enhance the generalizability of the results. Long-term investigations could offer deeper insights into how auditors' perceptions and attitudes towards AI develop over time. Moreover, incorporating objective measures, such as actual usage data of AI tools, could complement self-reported data and help mitigate potential biases. Expanding the theoretical framework to include additional factors, such as organizational support, regulatory influences, and specific attributes of AI technologies, could deliver a more extended interpretation of AI adoption in auditing. Finally, exploring the interaction between AI and human auditors in collaborative auditing environments could provide valuable insights into optimizing audit quality and effectiveness in the AI era. Addressing these areas in future research will further clarify the dynamics of AI integration in auditing, thereby guiding the profession towards more effective and efficient practices.

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